

Measuring the Generality of Nanotechnologies and its Potential Economic Implications

Fernando Gómez-Baquero
College of Nanoscale Science and Engineering, University at Albany
Albany, NY 12203 USA

Abstract—Technologies that have applications in a large number of sectors (general) have a more significant positive impact on economic activity in comparison to technologies that have applications in a few sectors (focused). The former are referred to in the economic literature as General Purpose Technologies (GPTs). Using patent data I conclude that nanotechnologies show one of the main characteristics of a GPT, high Generality, and I show the progression of their generality over the time period 1980-2008. A metric for generality is applied to compare nanotechnologies with other technologies previously identified as GPTs. The measurements show that ‘Nanotechnologies’ have a higher average Generality than semiconductors, and that the level of Generality of nanotechnologies has remained fairly constant for more than two decades. Technologies such as ‘Carbon Nanotubes’, and ‘Nanoparticles’ have a higher Generality than ‘Quantum Dots’. ‘Self-assembly’ appears to have transformed from a focused technology to a general purpose one. The choice of classification system used to calculate the Generality is relevant for the analysis of time trends. A high level of Generality in nanotechnologies is important to nanotech-intensive firms because it translates into a larger potential range of applications of their innovations. On the other hand, it also increases the possibility of competition from rivals that were previously developing focused technologies.

I. INTRODUCTION

In economic history technologies have played an important role in the process of economic growth. Moreover, a few key technologies appear to have driven technological and industrial progress in particular historical eras. The steam engine is an example of a technology that in the course of the 19th century became so important to industrial processes, that by the early 20th century it was virtually powering the entire industrial sector in the U.S. [1]. The wide impact of the steam engine in industrial processes occurred because it allowed energy to be transformed into continuous rotary motion, a generic function that spread to a wide range of applications that were the base for economic growth in the 19th century. Bresnahan and Trajtenberg [2] described in their seminal work how the “generic” quality of rotary motion resulted in the pervasiveness of the steam engine in economic activities.

They used the term General Purpose Technologies (GPTs) to describe technologies such as the steam engine that, because of their generic quality, could be used in a large variety of industrial products and production systems. Bresnahan and Trajtenberg [2] also noted that another important quality of a generic technology was its technological dynamism or its capacity to continuously improve its efficiency over time. This quality often results in reduced costs for the downstream sectors that use the technology, increasing their profitability and stimulating the use of the technology in more applications. Another GPT, electricity, illustrates more clearly how a GPT is not only pervasive in industrial sectors but also how it brings continuous improvements that stimulate its use in a large number of sectors. The process of electrification made possible to provide portable, distributed power to a great number of processes at a lower cost [3].

Bresnahan and Trajtenberg [2] identified a more recent example of a GPT found in the electronics era, with the introduction of semiconductor technologies and their general functionality: binary logic. With binary logic, standardization was practical and it allowed industrial savings and eventually performance increases in digital components [4]. Another recent technology that has been considered as a GPT is Information Technology (IT). Jovanovic and Rousseau [5] compare IT with electrification and state that IT also shows a high degree of pervasiveness among industrial sectors, continuous technological improvements, and the ability to spawn new innovations.

The question pertaining to this study is whether nanotechnologies can also be considered GPTs, or if they are becoming GPTs. To be able to answer this question and identify the possible GPT characteristics of nanotechnologies, it is first important to define GPTs and understand why nanotechnologies could be considered a new case of GPT.

II. WHY CAN WE THINK OF NANOTECHNOLOGIES AS GPTS?

A. Definition of a GPT

The current definition of a GPT comes from a compilation of more than two decades of growing literature [2, 5-8]. A GPT is defined as a technology that has the following characteristics:

- 1) *Pervasiveness*: a GPT should be used as an input in a wide range of sectors in the economy.

2) *Continuous improvement*: a GPT should improve upon itself over time, and should keep lowering the costs for its users.

3) *Innovation spawning*: a GPT should stimulate the invention of new products or processes in the user sectors and should drive complementarities in manufacturing or in the R&D sector.

The increased economic activity surrounding nanotechnology has motivated a number of researchers to further explore these characteristics in nanotechnologies, and is giving the opportunity to study how these symptoms emerge in a new technological field.

B. Previous Studies on Nanotechnologies as GPTs

Only a few works have tried to quantify and apply methods commonly used to examine other GPTs to nanotechnologies. An initial work by Huang et al. [9] suggested that nanotechnologies were GPTs by looking at the pervasiveness that nanotechnologies have had in patents issued between 1976-2002. Huang et al. applied several visualization techniques to understand the composition of a set of patents that were defined as nanotechnology-related. In their analysis, nanotechnology patents encompass a wide range of technology fields, with chemistry and molecular biology being the most prominent in patents issued.

Shea [10] also undertakes the analysis of nanotechnologies as GPTs from a managerial point of view. Nine propositions are developed to relate nanotechnology-based innovations to economic performance for incumbent firms. The theoretical evidence leads her to the conclusion that nanotechnologies are GPTs. Nevertheless, no quantitative methods like those used in previous works on GPTs were employed by Shea, prompting criticism by Porter, Shapira and Youtie [11].

A qualitative work linking nanotechnologies to GPTs was developed by Palmberg and Nikulainen [12]. They compare the development of nanotechnology with the development of biotechnology. They note that using the criteria of widening of uses and the range of its usability, nanotechnologies seem to perform like GPTs, but that it is still too early to know the extent to which nanotechnologies spawn *complimentary investments*.

In a recent work, Youtie, Iacopetta and Graham [13] undertake the task of finding evidence from patent data that can elucidate a GPT nature in nanotechnologies. They set to understand primarily the *pervasiveness* of nanotechnologies via a Generality measure based on the work of Trajtenberg et al. [14]. Youtie, Iacopetta and Graham applied this metric to a sample of patents classified as “nanotechnology patents”. Youtie et al. calculate the Generality Index for patents between 1990-1993, and compare the measurements obtained using USPTO, International Patent, and NBER Patent Database Technology Classes. Since the Generality Index is only informative when it is compared among a set of

technologies, they compare the measures for ‘Nanotechnology’ with ones for ‘Drugs’ and ‘Computers’. In their results, the Generality Index value for ‘Nanotechnology’ is very close to that of ‘Computers’, and much higher than the one obtained for ‘Drugs’. Youtie et al. state that the Generality measure can give insights into some characteristics of a GPT such as the “*pervasiveness*” and the “*coordination of beliefs*”, since the citation data in patents can be related to these characteristics.

This study aims to build upon these previous works by using patent data to measure a Generality Index for a selection of technologies. To better understand how this measure is constructed, it first is important to review some specificities of the measure of Generality.

III. MEASURING GPTS USING PATENTS

A. Generality

The question of how much information patents can provide about certain qualities of inventions, technologies, and in general of economic activity, can be traced back to the works of Griliches [15, 16]. But it was the work of Trajtenberg, Henderson and Jaffe [14] that laid the foundation for obtaining quantitative measurements from patents. In their work, Trajtenberg et al. defined an index for Generality:

$$G_i = GENERALITY_i = 1 - \sum_{k=1}^{N_i} \left(\frac{NCITING_{ik}}{NCITING_i} \right)^2 \quad (1)$$

for i patents, and where NCITING= number of patents citing the originating patent (“o-patent”). N =the number of different classes to which the patents belong, which can come from:

- 1) NCLASS= 3 or 4-digit original patent class.
- 2) CATCODE= 2-digit technological class (built by aggregating NCLASS).
- 3) FIELD= 1-digit classification by main technological fields.

The summation in G_i is equivalent to the Herfindahl Concentration Index. Therefore, G_i is simply a modified version of the Herfindahl Index. One important observation is that NCITING is biased downwards by the citations that are not yet observed. This is also referred to as a ‘lag’ effect, where ‘lag’ is defined as the difference in years between the issue date of a citing or cited patent, and the issue date of the o-patent [14]. Fig. 1 shows two examples of how this effect is seen in patents.

The lag effect tends to drive the Generality measurement down for newer patents. A bias correction was developed by Hall [17]. The correction takes the form

$$\tilde{G}_i = \frac{N_i}{N_i - 1} G_i \quad (2)$$

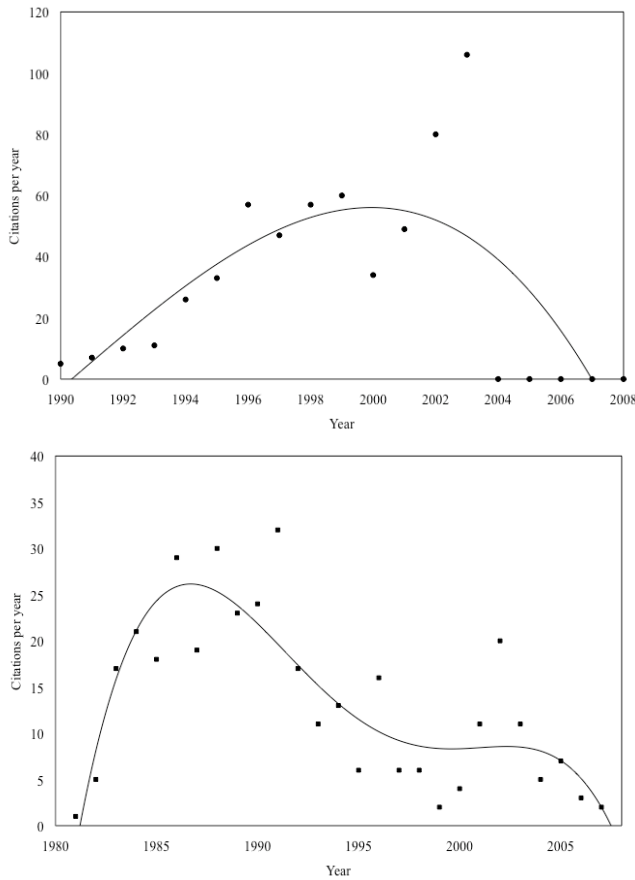


Fig. 1. Lag effects in patents for 'Semiconductors' (top) and 'Nanotechnologies' (bottom).

where N_i is the number of citations observed. This correction has been applied to all the Generality measures obtained throughout this work.

B. Choosing a Classification System

The choice of classes and classifications systems affects the measured Generality. Patents can be coded and classified by the United States Patent and Trademark Office (USPTO), by the European Patent Office (EPO), by the Japanese Patent and Trade Office (PTO) or by the World Intellectual Property Organization (WIPO), which uses an established International Patent Classification (IPC). Moreover, patents can also be classified using other types of established systems such as the Standard Industrial Classification (SIC) or the Derwent World Patent Index (DWPI) Classification System developed by Thomson Scientific.

This variety of options makes it difficult to compare the Generality measure obtained with values reported in other studies, since there is no certainty that the choice of classes made is perfectly equivalent. In the literature there appears to be no consensus on the type of classification system that should be used. For example, Hall and Trajtenberg [18] used SIC coding, Moser and Nicholas [19] used USPTO

classifications, and Youtie et al. [13] used UPSTO, IPC and NBER patent technology classes.

In this study, Generality measures were obtained using two classifications: the IPC classification at the 4-digit level (from here on referred to as IPC 4 digit) and the DWPI Classification System (from here on referred to as Derwent Class). The choice of two measuring using two different classification systems was made for comparative purposes. Table I shows the correlation of the Generality measurements obtained with both classification systems.

The correlations are different for each technological subject, with higher correlations for 'Semiconductors' and 'Nanotechnologies' and lower correlations for 'Proteomics' and 'Biotechnologies'. These correlations suggest that, for most technological subjects in this study, the results can be comparable across classifications systems.

Interpretations and analysis will be done individually for the technological subjects that present low correlation.

C. Choosing a Search Criteria

Another fundamental problem when measuring Generality is the choice of criteria for grouping patents. The chosen criteria are of great importance because they should generate a representative set of patents.

Porter, Youtie and Shapira [11] were among the first to state the need for an in depth study of the search criteria (or search terms) beyond the word 'nano', which was the search term chosen for patents and publications in previous works [9, 20, 21]. Porter, Youtie and Shapira [11] defined an improved search criteria by incorporating other relevant words such as 'monolayer', 'quantum dot', and 'AFM' among others. They also defined some exclusion terms that are relevant when the search string 'nano*' is used, for example, terms like 'nanoliter' or 'nanosecond'. This work was later followed by Mogoutov and Kahane [22] who published a comprehensive data search strategy for nanotechnology.

TABLE I
CORRELATIONS OF GENERALITY MEASUREMENTS

	Correlation between IPC 4 digit and Derwent Class
Semiconductors	0.61
Biotechnologies	0.28
Proteomics	0.10
Nanotechnologies	0.68
Carbon Nanotubes	0.42
Nanoparticles	0.43
Quantum Dots	0.34
Self Assembly	0.52

TABLE II
PATENT SEARCHES USING DIFFERENT CRITERIA

Search criteria	Number of patents
TI=(nanotech*)	133
TS=(nanotechnology)	542
TS=(nanotech*)	615
US Class 977 using Boliven.com	4,739
US Class 977 using USPTO Webstie (search term: CCL/977/S)	5,581
TI=((NANO* OR A*NANO* OR B*NANO* OR C*NANO* OR D*NANO* OR E*NANO* OR F*NANO* OR G*NANO* OR H*NANO* OR I*NANO* OR J*NANO* OR K*NANO* OR L*NANO* OR M*NANO* OR N*NANO* OR O*NANO* OR P*NANO* OR Q*NANO* OR R*NANO* OR S*NANO* OR T*NANO* OR U*NANO* OR V*NANO* OR W*NANO* OR X*NANO* OR Y*NANO* OR Z*NANO*) NOT (NANO2 OR NANO3 OR NANO4 OR NANO5 OR NANOSECOND* OR NANOLITER*))	43,149
TI=(nano*)	43,180
TS=(nano*)	72,853

Timespan used for all databases=all years

In addition to the published efforts on refining search terms for nanotechnologies, patent offices have started to insert tracking classes to identify patents related to nanotechnology. Currently, the USPTO uses Class 977, the European Patent Office (EPO) uses Class Y01N, the Japanese Patent and Trade Office (PTO) uses Class ZNM, and in the International Patent Classification the class used is B82 [13].

Table II presents a comparison of the search results for nanotechnologies using different search criteria. The choice of search string greatly influences the sample obtained. Some search terms for nanotechnologies may overly restrict the sample, while other might include a number of records not relevant for the desired analysis. Additionally, ISI/WoK allows for the search string to retrieve patents according to their patent title (TI) or to their patent title subject (TS).

Mogoutov and Kahane [22] reported a difference of over 45,000 references in a single year between two databases that were used to study emerging technologies. This difference is in part given by the definitions used to extract and collect data.

The search criteria proposed by Mogoutov and Kahane [22] produces search sets which not only include a relevant set of patents to analyze, but also manage to correct for records that might not correspond to the desired technological subject. For the purpose of this work, the search criteria used follow closely the search terms defined by these authors.

IV. GENERALITY MEASUREMENTS FOR NANOTECHNOLOGIES AND OTHER SELECTED TECHNOLOGICAL FIELDS

A. Methodology

Patent data was obtained using ISI Web of KnowledgeSM (ISI/WoK) from Thomson Scientific – Thomson Reuters. For this study the set obtained covers patents within the time span 1980-2008. The post-1980 time frame is a limitation of the ISI/WoK Database.

In order to establish the *pervasiveness* of nanotechnologies, a comparison must be made with another set of technologies that is regarded as a GPT. ‘Semiconductors’ was chosen as a

GPT, along with other technological subjects that would serve for comparison purposes. ‘Biotechnology’ and ‘Proteomics’ were chosen as technological subjects given that other reports [12, 23, 24] have suggested that the emergence of some nanotechnologies is following similar paths as the one followed by biotechnologies and proteomics. Additionally, more detail technological subjects related to nanotechnology were used to further explore the differences between an aggregate term such as ‘Nanotechnologies’ and a more specific subject, such as ‘Carbon Nanotubes’, ‘Nanoparticles’, ‘Quantum Dots’ or ‘Self-Assembly’.

The selected set of technological subjects for this study and their corresponding search criteria can be seen in Table III. The search criteria used for ‘Nanotechnologies’ is the one suggested by Mogoutov and Kahane [22], and the other search terms used are similar or derivations of the search terms suggested by the same.

B. The Sample

The sample obtained comprises patents published by the USPTO, the EPO and the Japanese Patent Office. For all patents, their IPC (4 digit codes) was extracted along with the DWPI Class (3 digit code).

Table IV shows the composition of the set of patents used. For each technological subject, the set of the 1,000 most cited patents was retrieved. For some technological subjects such as Biotechnology, Proteomics, Quantum Dots and Self-Assembly, less than 1,000 patents were found to have at least 2 citations. The choice of the top 1,000 patents was made to generate a sample that was representative of the technological subject to be studied. For some of the selected subjects the choice of top 1,000 acquired almost all, if not all patents for which Generality is defined. For the most extensive technological subjects such as ‘Semiconductors’ and ‘Nanotechnologies’ the choice may retrieve a small percentage of the total patents, but it within the patents obtained there is a good distribution of Generality measurements, suggesting that the sample is representative of the overall behavior of the technology.

TABLE III
SEARCH TERMS AND SEARCH STRINGS USED

Technological subject	Search String
Semiconductors	TI=(semiconduct*)
Biotechnology	TS=(biotechnology)
Proteomics	TS=(proteom*)
Nanotechnologies	TI=((NANO* OR A*NANO* OR B*NANO* OR C*NANO* OR D*NANO* OR E*NANO* OR F*NANO* OR G*NANO* OR H*NANO* OR I*NANO* OR J*NANO* OR K*NANO* OR L*NANO* OR M*NANO* OR N*NANO* OR O*NANO* OR P*NANO* OR Q*NANO* OR R*NANO* OR S*NANO* OR T*NANO* OR U*NANO* OR V*NANO* OR W*NANO* OR X*NANO* OR Y*NANO* OR Z*NANO*) NOT (NANO2 OR NANO3 OR NANO4 OR NANO5 OR NANOSECOND* OR NANOLITER*))
Carbon Nanotubes	TI=(nanotub* AND carbon)
Nanoparticles	TI=(nanoparticl*)
Quantum Dots	TI=(quantum dot*)
Self Assembly	TI=(self-assembly)

TABLE IV
SEARCH, SAMPLE AND GENERALITY STATISTICS

Search Statistics	Semiconductors	Biotechnology	Proteomics	Nanotechnologies	Carbon Nanotubes	Nanoparticles	Quantum Dots	Self Assembly
Total Patents 1980-2009	577,226	5,504	1,306	41,983	5,050	5,526	1,180	373
Patents with more than 1 citation	159,065	927	430	6,679	1,008	520	273	88
Patents without citations	327,349	3,986	686	31,780	3,537	3,870	792	234
Sample Statistics								
Patents in the sample	1000	927	430	1,000	1,000	520	273	88
Sample as percentage of total records	0.2%	16.8%	32.9%	2.4%	19.8%	9.4%	23.1%	23.6%
Sample as percentage of records with more than 1 citation	0.6%	100%	100%	15.0%	99.2%	100.0%	100%	100%
Maximum citations	1000	197	99	359	141	101	109	143
Minimum citations	78	2	2	17	4	4	2	2
Generality Statistics								
IPC 4 digit								
Average Generality	0.51	0.96	1.07	0.78	0.92	0.90	0.87	0.92
Standard Deviation	0.24	0.61	0.58	0.22	0.17	0.26	0.62	0.62
Derwent Class								
Average Generality	0.65	0.90	0.72	0.81	0.93	0.87	0.92	0.94
Standard Deviation	0.18	0.62	0.64	0.17	0.18	0.28	0.62	0.65

Note that Generality is not defined for patents without citations, and is by definition 0 when a patent has only 1 citation. In this work such patents have been omitted following the methodology of Hall and Trajtenberg [18].

Fig. 2 shows how the number of citations in the top 100 most cited patents (No. 1 being the most cited) drops sharply for all subjects in the sample. ‘Semiconductors’ has the most cited patent with 1,000 citations, followed by ‘Nanotechnologies’ with 359 citations.

For each patent within each of the 8 technological subjects, the Generality Index was calculated using the measurement described in section III. Fig. 3 shows how the Generality varies heavily across the samples taken. For the sets that contain highly cited patents there seems to be no correlation between the number of citations and the Generality. This is seen in the ‘Semiconductors’ and ‘Nanotechnologies’ samples, where high and low values of Generality occur among highly cited patents. All other technology subjects show a decreasing trend in generality as the number of citations decreases. These results contradict in part a reported observation that the highly cited patents “*have a higher generality, no matter how generality is measured*” [18]. Highly cited patents in this sample have both high and low Generality. As the number of citations approaches very small numbers it is seen that on the average the measured generality is lower. However, the set of ‘Nanotechnologies’ shows that patents that have a relatively low number of citations (between 30 and 20 in this case) can still have as high Generality as patents with more than 100 citations.

The sample also has large standard deviations of the Generality measurements. High standard deviations are also observed when using the Derwent. In fact, values are very similar for each technological subject, with the exception of the ‘Semiconductor’ sample. This could indicate that a wide distribution of values could have a contribution due to the method of classification factor. For most of the studied sample in this work though, that contribution seems to be small.

C. Time Trends of Generality

Time trends were obtained by averaging the Generality measures for patents that were issued in the same year. This has some statistical implications that must be considered. The first one is that the number of patents, taken each year to calculate the average of Generality Index, is not the same and may not even be evenly distributed. This may bias some of the yearly averages, either by making them a single point or by biasing the Generality downward because of the likelihood that a small set of patents for a year would be related to patents with fewer citations. A second result of averaging over the acquired sample set is that the time trends often show high standard deviations.

Fig. 4 show how these effects can be visualized in the time series of Generality averages. Using both IPC 4 digit and Derwent Classification, a very broad standard deviation can be seen across all technological subjects. Some technological subjects also show signs of the lag effect and the downward bias effect described in the literature [17, 18], mostly after 2001.

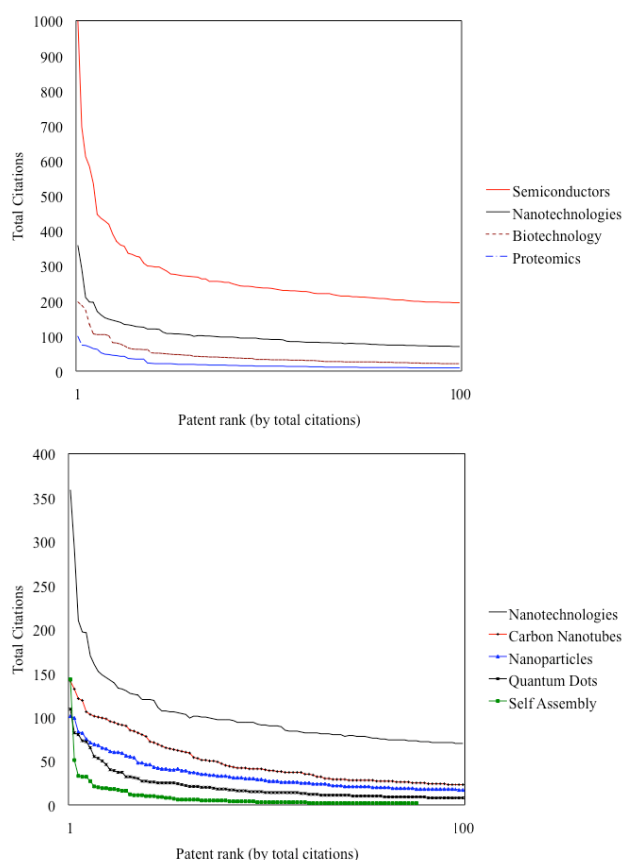


Fig. 2. Distribution of the top 100 most cited patents by technological subject

Fig. 5 is a compilation of the time trends of the averaged Generality for the selected technological subjects, using the IPC 4 digit classification. Comparing 'Semiconductors' and 'Nanotechnologies' there seems to be two distinct periods of time: prior to 1990 where on the average the Generality of both are similar, and a period after 1990 where the generality of 'Nanotechnologies' has remained above the one of semiconductors. 'Biotechnology' has a very similar Generality trend to 'Nanotechnologies', except for a period of time around 2001 where the Generality of 'Biotechnology' dropped. 'Proteomics' has a very high Generality, very similar to the one of 'Nanotechnologies'. 'Proteomics' also has an interesting upward trend for the last year in the sample, a result not expected due to the bias effect.

Over the set of nanotechnologies, 'Carbon Nanotubes' have higher average generalities when compared to both 'Nanotechnologies' and 'Semiconductors'. The time progression for 'Nanoparticles' shows an increase in Generality since 1994 with a peak around 2006. This would suggest that 'Nanoparticles' started as a focused technology and have progressively become more a general purpose one. 'Quantum Dots' appear to have started as a very general

technology and to have stabilized in a somewhat high level of generality.

The case of 'Self-Assembly' is interesting because there is a great variability during the first decade, and a stabilization and rise over the next two decades.

Although the high standard deviations must be kept in mind, these trends are in accordance with some observations of how these technologies have evolved. For example, one could expect a high Generality for technologies such as 'Carbon Nanotubes' and 'Nanoparticles', technologies that have been regarded as revolutionary and disruptive. Perhaps the increase in Generality for 'Quantum Dots' over the last few years has to do with how their use and applications in fields beyond medical imaging has evolved.

An interesting observation is that the averages of Generalities seem to have a greater variability for the period prior to 1995, for all technological subjects. This could occur either because the emerging technology has not yet matured as a field of industrial applications, or simply because of the way patents are classified.

A good comparison is obtained when the same time analysis is performed using the Derwent Classification (Fig. 6). Using Derwent Classes, there seems to be less of a disparity between the Generality averages of 'Nanotechnologies' and 'Semiconductors'. 'Semiconductors' show a sharp drop after 2001, which was not seen when averaging using IPC 4 digit classes. 'Nanotechnologies' show a greater average Generality than both 'Biotechnology' and 'Proteomics'.

'Nanotechnologies' appear to have a greater average Generality than 'Semiconductors', 'Biotechnology' and 'Proteomics' particularly after 1990. The Derwent Classification gives similar trends for the set of nanotechnologies. Overall, both classifications systems show that 'Nanotechnologies' consistently have a greater Generality than 'Semiconductors' and that particular nanotechnologies either have a high Generality or are growing on Generality.

Comparing the averages obtained with IPC 4 digit and Derwent Class, it can be seen that Derwent Class has a smaller variability in the measured averages in the period prior to 1990. This could be an indicator that some of the variability of the measures in the 1980s decade is given by the classification of the patents. 'Self Assembly' and 'Quantum Dots' have a greater variability than 'Carbon Nanotubes' and 'Nanoparticles'. The interesting trend for 'Carbon Nanotubes' where it increases rapidly to stabilize in a relatively high Generality, could be consistent with the fast discovery of applications immediately following their discovery. For 'Nanotechnologies' the average generality over the period is fairly constant.

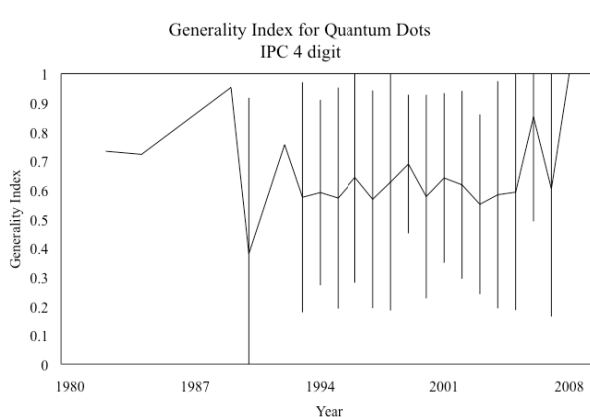
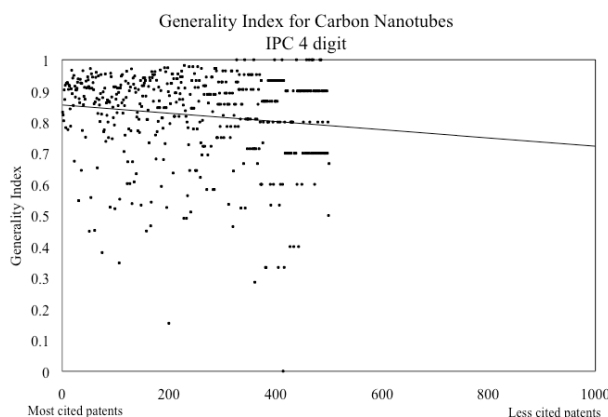
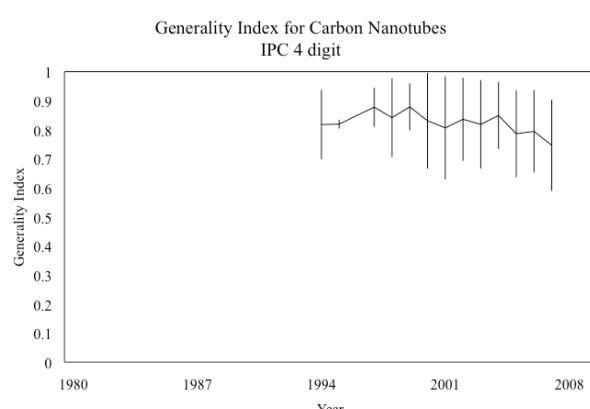
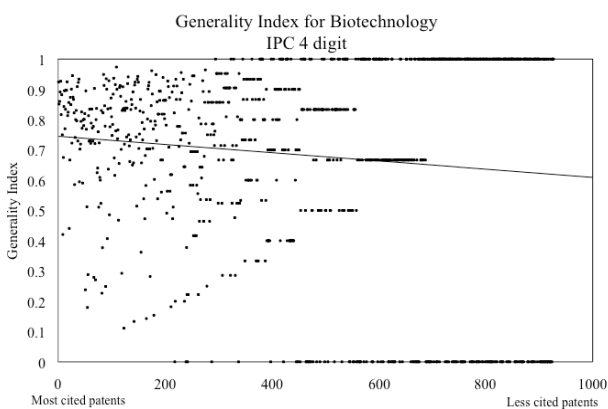
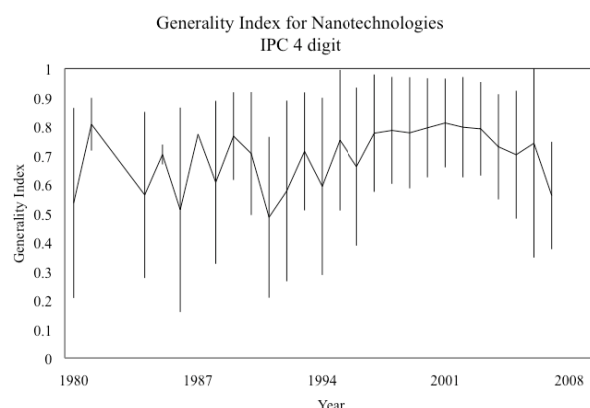
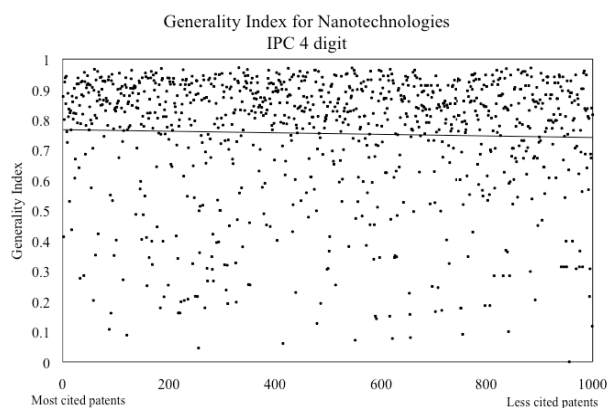
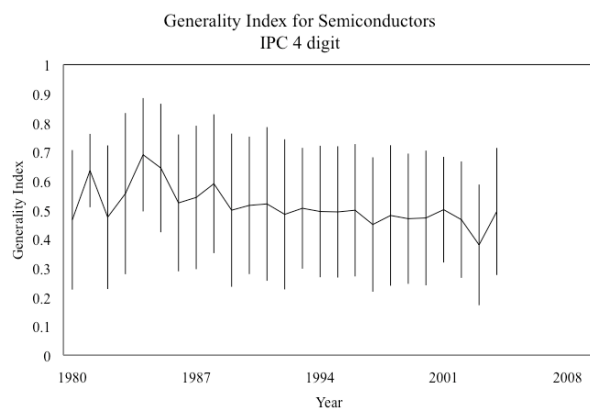
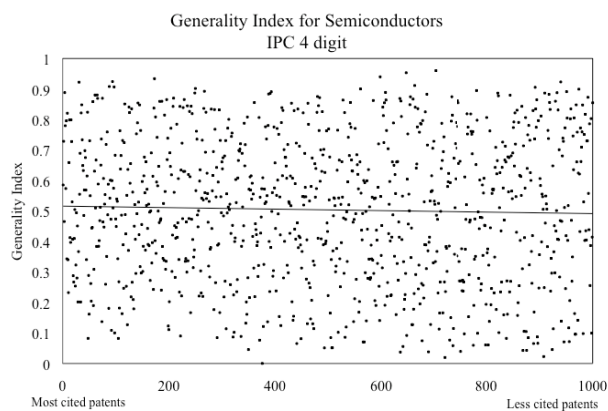


Fig. 3. Generality measurements of selected technology subjects.

Fig. 4. Time trends of Generality (bars correspond to the standard deviation).

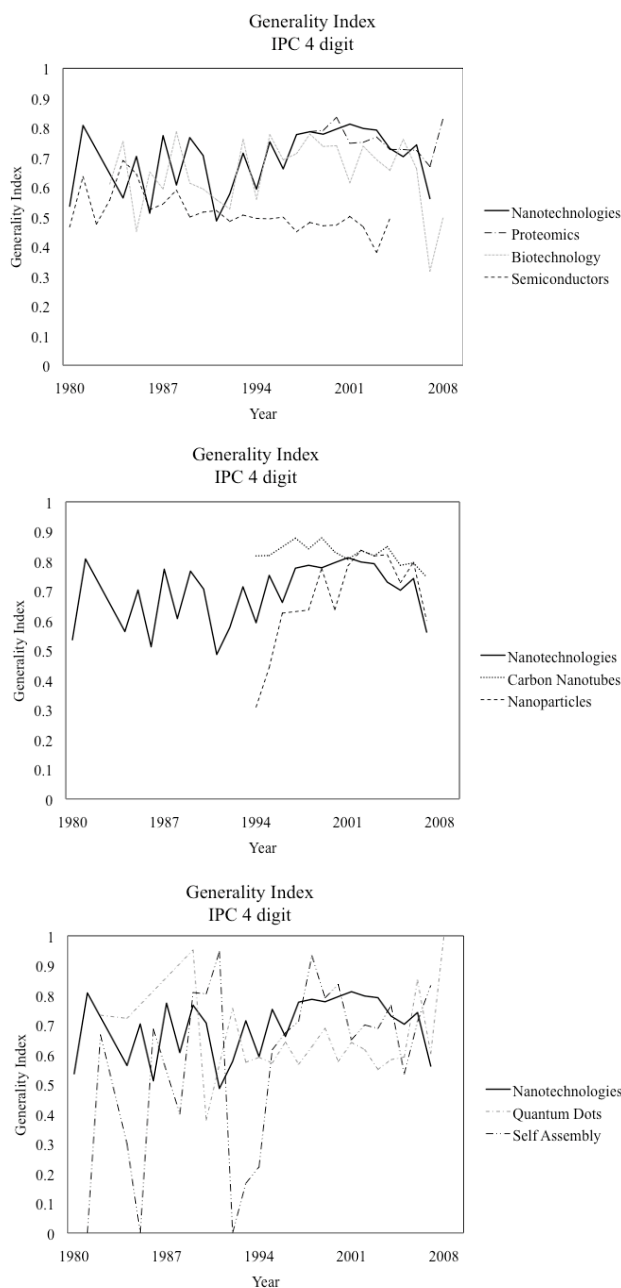


Fig. 5. Generality Index time trends of selected technology subjects using IPC 4 digit classes.

V. ADDITIONAL COMMENTS ON NANOTECHNOLOGIES AS GPTS

Measures of Generality can give some insight into the *pervasiveness* of a set of new technologies, but the definition of GPTs also includes characteristics such as ‘*innovation spawning*’ and ‘*continuous improvement*’ that are not directly related to the Generality Index. However, one could look at other studies to complement the analysis and shed light towards the GPT nature of nanotechnologies. For example,

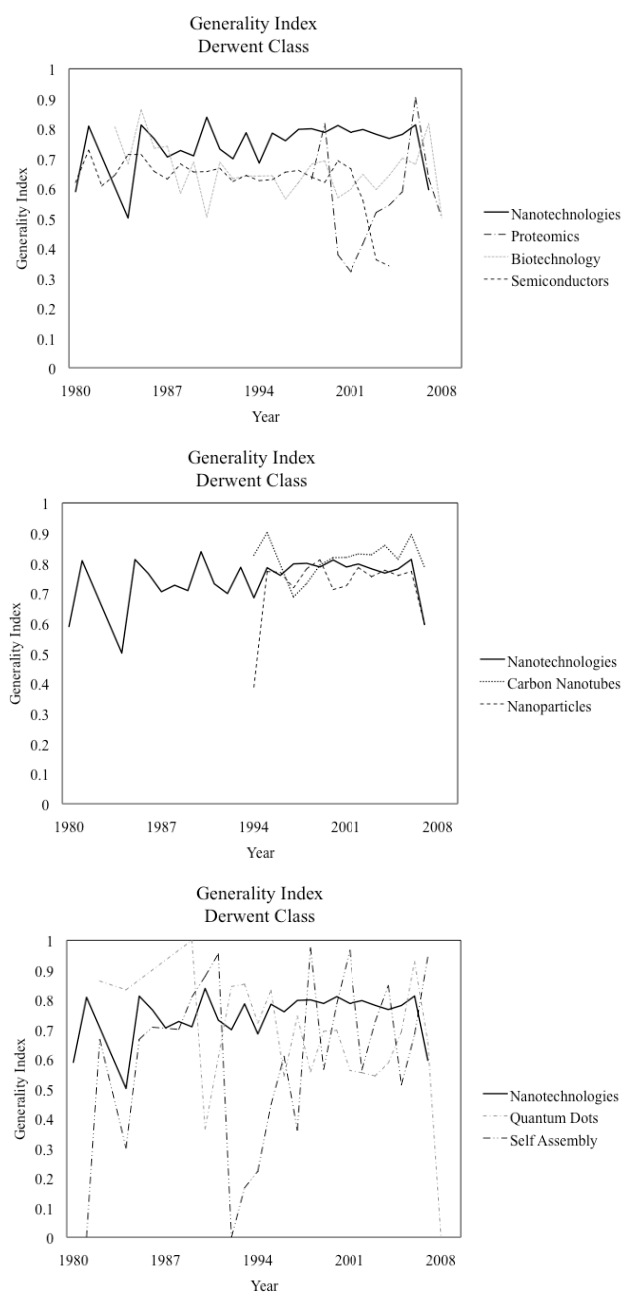


Fig. 6. Generality Index time trends of selected technology subjects, using Derwent Classes.

private firms and national agencies have forecasted a market for nanotechnology-enabled products of \$2.6 trillion in as little as 5 years [25]. Given these commercial prospects, government agencies and companies have given to nanotechnology-related research billions of dollars to create a new set of innovative technologies. This could be considered as an ‘*innovation spawning*’ effect of nanotechnologies, which clearly seen when looking at the numbers of patents and publications produced: in the period between 1976-2006 more than 7,400 patents related to nanotechnology were granted by the United States Patent and Trademark Office (USPTO)

alone, with more than 1,200 patents being issued worldwide [26]. Publications related to nanotechnology have also had an exponential growth, going from 1,881 in 1990 to almost 56,000 in 2005 [11]. Several authors have stated the importance gained by nanotechnologies in recent years, has been fueled by proven technological breakthroughs [12, 13, 27, 28]. Most of these reports are based on the interesting *performance improvements*, which in turn have fueled more scientific research. Perhaps one needs to look no further than the semiconductor industry to understand how nanotechnologies are bringing continuous improvements: it is the ability of the industry to fabricate below the 100nm dimensions that has maintained the pace of Moore's Law for more than a decade.

VI. CONCLUSIONS

The Generality measures obtained in this study suggest that 'Nanotechnologies' have the pervasiveness characteristic of GPTs, measured as a higher average Generality than Semiconductors and other technological subjects. The average Generality of 'Nanotechnologies' has remained high and constant for more than two decades. Not all nanotechnologies are the same however. 'Carbon Nanotubes' and 'Nanoparticles' have greater average Generality than 'Quantum Dots' or 'Self Assembly'. 'Nanotechnologies' also seem to be different than other technological booms (i.e. 'Biotechnology' and 'Proteomics'), with more average Generality and less variability in the past decade.

The results of this work should encourage firms and public institutions to keep tracking the development of the Generality of the emerging nanotechnologies. Choosing to develop nanotechnologies with a high level of Generality is important to nanotech-intensive firms because it translates into a larger potential range of applications of their innovations. On the other hand, it also increases the possibility of competition from rivals that were previously developing focused technologies. Further studies are needed not only to expand the tracking of the Generality of these emerging technologies, but also to develop more quantitative methods that can help to elucidate more aspects of the GPT nature of nanotechnologies.

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